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ORIGINAL PAPER

Classification of features selected through Optimum Index Factor (OIF) for improving classification accuracy

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Abstract: The present investigation was performed to determine if the features selected through Optimum Index Factor (OIF) could provide improved classification accuracy of the various categories on the satellite images of the individual years as well as stacked images of two different years as compared to all the features considered together. Further, in order to determine if there occurs increase in the classification accuracy of the different categories with corresponding increase in the OIF values of the features extracted from both the individual years' and stacked images, we performed linear regression between the producer's accuracy (PA) of the various categories with the OIF values of the different combinations of the features. The investigations demonstrated that there occurs significant improvement in the PA of two impervious categories viz. moderate built-up and low density built-up determined from the classification of the bands and principal components associated with the highest OIF value as compared to all the bands and principal components for both the individual years' and stacked images respectively. Regression analyses exhibited positive trends between the regression coefficients and OIF values for the various categories determined for the individual years' and stacked images respectively signifying the prevalence of direct relationship between the increase in the information content with corresponding increase in the OIF values. The research proved that features extracted through OIF from both the individual years' and stacked images are capable of providing significantly improved PA as compared to all the features pooled together.

Key words: OIF; supervised classification; principal components; band combinations

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Introduction

Remote sensing image classification can be viewed as a joint venture of both image processing and classification techniques. Generally, image classification, in the field of remote sensing is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixels found in remotely sensed data into classes that match the informational categories of user interest by comparing pixels to one another and to those of known identity (Palaniswami et al. 2006; Perumal and Bhaskaran 2010). Several methods of image classification exist and a number of fields apart from remote sensing like image analysis and pattern recognition make use of this significant concept of classification. In some cases, the classification itself may form the entity of the analysis and serve as the ultimate product. In other cases, the classification can serve only as an intermediate step in more intricate analyses, such as land-degradation studies, process studies, landscape modeling, coastal zone management, resource management and other environmental monitoring applications. Generally, remote sensing offers imperative coverage, mapping and classification of land-cover features, namely vegetation, soil, water and forests. A principal application of remotely sensed data is to create a classification map of the identifiable or meaningful features or classes of land cover types in a scene (Jasinski 1996).

Multispectral digital classification of remote sensing data with several spectral bands requires a judgment prior to final classification about spectral bands which are most effective, accurate and economical in separating each class from all others. There are several approaches for selection of features from multispectral datasets that could provide the optimum information about the various categories present within a scene. One of them is the selective principal components analysis (Siljestrom *et al*. 2002) that deals with the selection of the most informative principal components based on their eigenvalues. Many a times, classification of the selective principal components yields better classification accuracy of some of the categories as compared to the clas-

sification of all the principal components. This is conceptually possible because the spectral properties of some of the categories can be better explained by a few principal components rather than by all of them. Another effective technique of the selection of the most informative features is the Optimum Index Factor (OIF) based on the maximum information content of the bands from a multispectral data (Chavez et al. 1982; Chavez et al. 1984). OIF helps in selection of suitable three-band combination for generation of FCC having optimum information (Saha and Kudrat 1991). High value of OIF indicates that the bands contain much information (e.g. high standard deviation) with little duplication (e.g. low correlation between the bands). In addition to the selective principal component analysis and OIF, stacked images of two different years have proved to be successful in providing significantly better information than the images of the individual years. Stacking facilitates aggregation of the spectral information from two different years thereby explaining the spectral variability of the different categories in a more correct manner. Classification of the stacked images is therefore expected to provide better classification accuracy of some of the categories.

In the present study, we have employed Optimum Index Factor technique for selecting the best combination of the features from three individual years' images of 1996, 2004 and 2009 of Ranchi area, India and from two sets of stacked images, the first one comprising the images of 1996 and 2004 and the second one those of 2004 and 2009 respectively for performing further classification on them and subsequently, carried out delineation of comparison of the classification accuracy yielded by the OIF based features with that by the individual years' images and stacked images. The present study was performed with the following aims and objectives: (1) to determine the best three-band combination of the spectral bands of the images of the individual years' and stacked images based on their OIF values; (2) to determine the producer's accuracy of the various pervious and impervious categories from the classification of the various three-band combinations of bands and the principal components extracted from the individual three-band combination of bands; (3) to delineate comparison between the producer's accuracy determined from the classification of three-band combination with the highest OIF value and the principal components extracted from this combination of bands with that obtained from all the bands and all the principal components corresponding to the images of the individual years' and stacked images of the respective years; (4) To derive the regression coefficients between the producer's accuracy of the different categories determined from the classification of the various three-band and three-PC combinations and the corresponding OIF values in order to assess the relationship between the producer's accuracy and OIF values.

Material and methods

Study Area

The area considered for performing the present investigation includes Ranchi city and its surroundings which is also the capital of the Jharkhand state, India and is bounded by 23°16'28" N to 23°27'34" N and 85°18'14" E to 85°26'54" E (Fig 1). The study area forms part of the Chotanagpur region and is located at an altitude of 654 meter above the mean sea level. The area is traversed by Subarnarekha river and its major tributaries viz. Jumar, Potpoto, Sapahi etc. and is characterized by the occurrence of dense dendritic drainage network. The type of forest found in this region is Dry Peninsular and includes important trees like Sal, jack, bamboo thickets etc. In Ranchi the forest cover is dwindling very fast because of the clearance of the jungles by the aboriginals for cultivation.

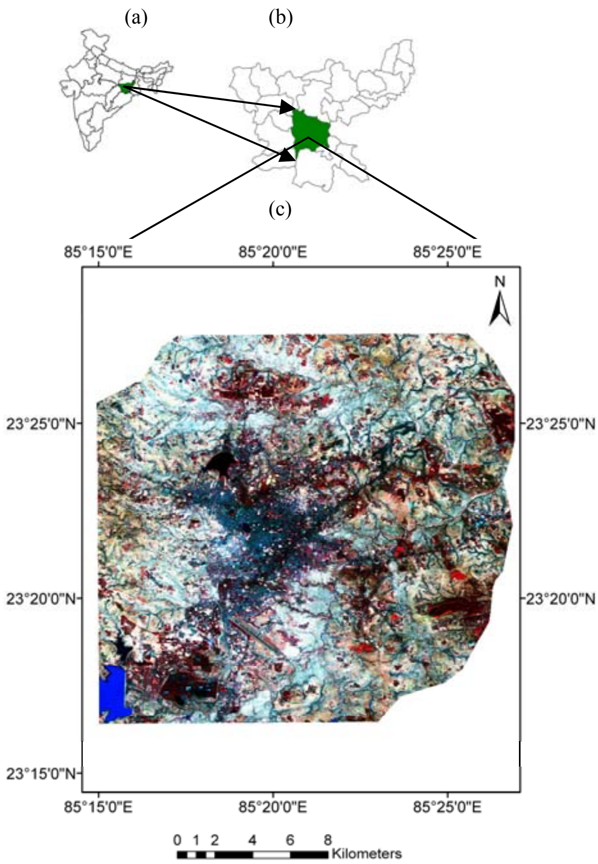

Fig 1. Study area (a) map of India, (b) map of Jharkhand, (c) Satellite imagery of study area.

Geographically the study area is largely heterogeneous resulted from the occurrence of urban built-up agglomerate of varying density and types of dwellings, agricultural lands, barren lands, natural vegetation comprising forest, shrub etc. and numerous standing water bodies such as ponds. As per census, from 1901 to 1941 the rate of growth was 3.5% per annum, whereas it was 14% during 1951 to 1971 and 8% during 1971 to 2001. After independence, the population of Ranchi City in 1951 was only 106 849, which increased by over eight times to 863 180 in 2001 (Singh SK. 2006). In the study area, agriculture has remained at subsistence level; large tracts of land are left barren which are highly fertile for the cultivation of pulses and vegetables. Paddy dominates the present cropping pattern followed by

pulses, maize and wheat. The main problems facing at present in the study area are rapid and unscientific and unsustained urbanization at the expense of the fertile agricultural lands and natural vegetation with the former being more vulnerable due its occurrence within the main city area and in the immediate surroundings of the main city area. This has caused drastic modification in the landscape in addition to triggering many adverse effects such as increase in the extent of the impervious features, decrease in the rain water recharge, lowering of the ground water table, increase in the temperature and various other ecological problems related to biodiversity loss and increase in air, noise and surface water pollution. If the present pace of urbanization persists, the ecological paradigm of the study area will worsen to such extent that it will be nearly impossible to restore its pristine status. In order to carry out quantitative assessment of the ecological status of the study area and implement necessary remedial strategy, it is imperative to carry out spatio-temporal monitoring and assessment of the land use and land cover dynamics using reliable yet fast techniques such as the digital classification of the multispectral remote sensing data.

Data Used

The data used in this study are namely the IRS LISS III data of December 1996 pertaining to the pre-capital formation period and IRS LISS III data of February 2004 and February 2009 that represent the post-capital formation periods respectively. Ranchi city was formed as the capital of the Jharkhand state in the year 2000 after which the study area witnessed rapid urbanization. The LISS III data is characterized by spatial resolution of 23.5 m, four spectral bands with band width of 0.52–0.59 µm, 0.62–0.68 µm, 0.77–0.86 µm, 1.55–1.70 µm and temporal resolution of 24 days that enables proper identification and delineation of the different land use and land cover categories considered in the present research such as agricultural land, natural vegetation, barren land, standing water bodies, dense built-up, moderate built-up with or without vegetation and low density built-up with or without vegetation.

Methodology

The satellite data of the individual years were georeferenced with the help of the GCPs identified on the corresponding Survey of India toposheet No. 73E/7. Two types of datasets were used for performing optimum index factor technique in the present study such as (1) the images of the individual years and (2) stacked images of two successive year's data. In addition, the principal components were generated from the three bands of each three-band combination of the images of the individual years and the two stacked images. From the images of the individual years each comprising four spectral bands, four three-band combinations were formed (i.e. bands 1 2 3, 1 2 4, 1 3 4, and 2 3 4) while from each of the stacked images comprising eight spectral bands, 56 three-band combinations were possible. OIF value of each of the three-band combinations was computed. However, we considered only 48 such combinations for each of the stacked images by ignoring the band-combinations having the same OIF values. The principal components of each of the three-band combinations were determined. The OIF values of the various three-band combinations for the images of the individual years and stacked images are listed in Table 3. In the next step, producer's accuracy of different land use and land cover categories were determined from the supervised maximum likelihood based classification of each of the three-band combinations by considering their training signatures extracted from the different types of datasets as mentioned above. On the stacked images extraction of the training signatures for the individual categories was done by ascertaining their presence in the images of both the years. The training signatures extracted from the stacked images gathers the spectral information from twice the number of the spectral bands contained in the image of an individual year with each spectral band repeated twice. As a result, the training signatures of the stacked images are capable of providing more accurate spectral information of the various categories thereby facilitating significant improvement in their producer's accuracies. The producer's accuracy determined from the classification of the three-band combination with the highest OIF and the principal components extracted from this band combination for the various categories was compared with that determined from the classification of all bands data and all principal components corresponding to the images of the individual years and stacked images. Regression analysis was performed between the producer's accuracy of the different categories determined from the classification of various three-band combinations and their OIF values in order to determine if there exists any correlation between them.

The Optimum Index Factor (OIF) to determine the most informative three-band combination is determined by the following formula.

$$\mathrm{OIF} = \mathrm{Max}\left(\frac{\sum_{i=1}^{n} \sigma(i)}{\sum_{j=1}^{n} |\, r(j)\, |} \right)$$

where OIF is the optimum index factor, σ (i) is the standard deviation of ith band, r (j) is the value of correlation coefficient between any two bands.

Discussion

The results derived from the investigations carried out in the present study are presented in two sections.

Comparison between the producer's accuracy determined from the classification of the features selected through OIF and original images

Comparative analyses among the producer's accuracy of the various categories determined from the classification of the three-band combination having the highest OIF value and the

principal components generated from this band combination for the images of the individual years 1996, 2004 and 2009 reveal that except natural vegetation the remaining pervious categories exhibit nearly 100% producer's accuracy in all the years (Tables 1, 2 and Fig 2). Natural vegetation also shows producer's accuracy of 100% in the year 1996; however in the other two years it is nearly 97% that is found to be higher than the producer's accuracy yielded by all the bands (Table 5). On the other hand, there also occurs an increase in the PA of this category in the PCs as compared to the bands that signifies the potential of the PCs in improving the classification accuracy.

Among the impervious categories, dense built-up is associated with the highest accuracy although the PCs exhibit higher accuracy than the bands. Moderate built-up category is characterized by the lowest classification accuracy in the bands that significantly improves in the corresponding PCs. Similar observation is found with the low density built-up category. It is to be noted that the PA of these two categories are higher than those determined from the classification of all the bands and all the PCs (Tables 5 and 6).

The PA of the various pervious categories determined from the classification of the two stacked images is found to be 100 percent except agriculture and natural vegetation in the stacked images of 1996-2004 and 2004-2009 respectively. However, in the PCs of the stacked images, the PA of all the pervious categories becomes 100 percent (Tables 3, 4 and Fig 2). Among the various impervious categories, dense built-up exhibits the highest PA in both the stacked images and their PCs. However, the moderate density built-up and low density built-up categories are characterized by significantly lower PA in the bands that however improves considerably in the corresponding PCs. The classification accuracies provided by the features selected through OIF are significantly higher than that determined from the classification of all the bands and all the PCs of the respective stacked images (Tables 5 and 6).

Table 1. Summary of the producer's accuracy of the different land use and land cover categories determined from the classification of the three-band combination images of the individual years i.e. 1996, 2004 and 2009 respectively associated with the highest OIF values (AG: Agriculture; NV: Natural Vegetation; BL: Barren Land; SW: Standing Water; DB: Dense Built-up; MDB: Moderate Density Built-up; LDB: Low Density Built-up) .

Year	Band combination	OIF	Categories						
			AG	NV	BL	SW	DB	MDB	LDB
1996	134	22.98	100	100	100	100	95.85	79.61	79.55
2004	134	23.47	98.96	97.29	100	99.62	90.94	74.45	73.63
2009	134	22.23	98.81	96.98	100	100	94.77	64.97	77.36

Table 2. Summary of the producer's accuracy of the different land use and land cover categories determined from the classification of the three-PC combination images of the individual years i.e. 1996, 2004 and 2009 respectively generated from their corresponding three-band combination images associated with the highest OIF values.

Year	Band combination	OIF	Categories						
			AG	NV	BL	SW	DB	MDB	LDB
1996	134	22.98	100	100	100	100	99.85	90.95	89.85
2004	134	23.47	97.91	99.11	100	99.98	95.94	85.45	89.36
2009	134	22.23	99.78	97.06	100	100	97.75	85.15	92.62

Table 3. Summary of the producer's accuracy of the different land use and land cover categories determined from the classification of the three-band combination images associated with the highest OIF values corresponding to the stacked images of 1996-2004 and 2004-2009 respectively.

Year	Band combination	OIF	Categories						
			AG	NV	BL	SW	DB	MDB	LDB
1996-2004	458	32.02	96.98	100	100	100	96.89	85.24	76.11
2004-2009	814	34.02	99.92	94.81	100	99.98	94.31	53.54	62.87

Table 4. Summary of the producer's accuracy of the different land use and land cover categories determined from the classification of the three-PC combination images derived from the three-band combination associated with the highest OIF values corresponding to the stacked images of 1996-2004 and 2004-2009 respectively.

Year	Band combination	OIF	Categories						
			AG	NV	BL	SW	DB	MDB	LDB
1996-2004	458	32.02	99.95	99.99	100	100	99.78	93.05	98.34
2004-2009	814	34.02	100	100	100	100	99.78	93.05	98.34

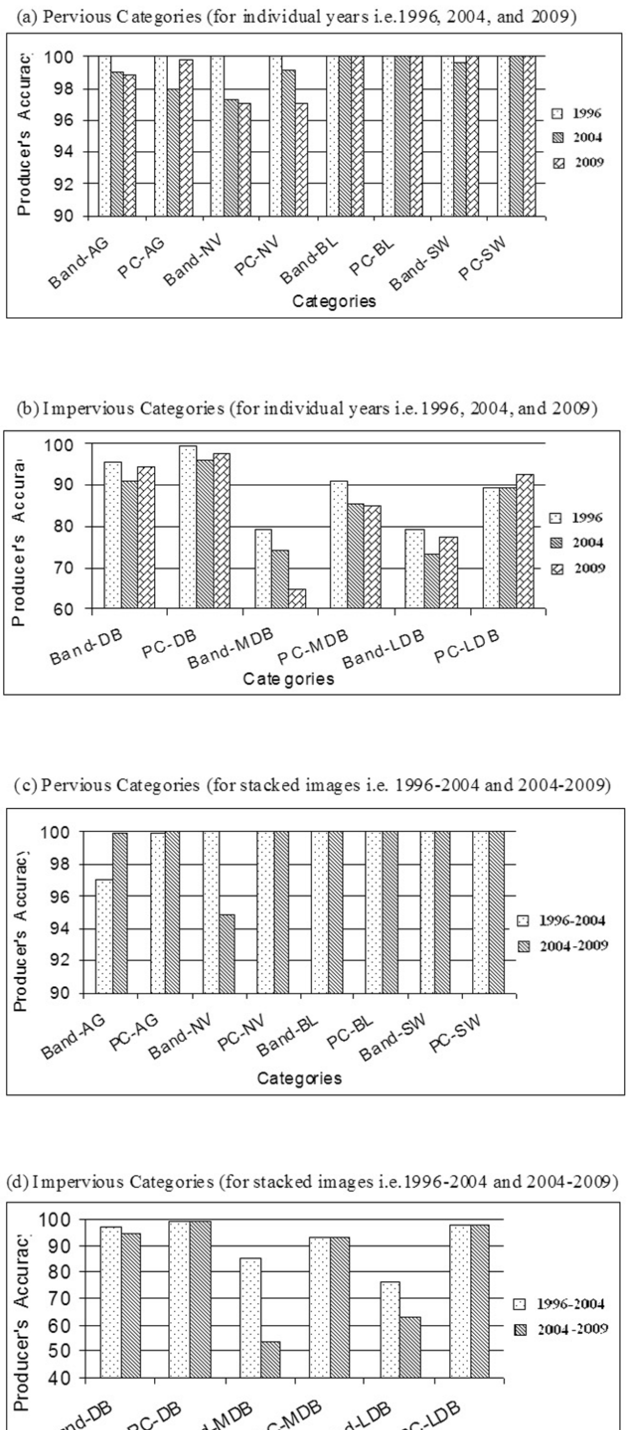

Fig 2. Producer's accuracy of the various pervious and impervious categories determined from the classification of the three-band combination images of the individual years (i.e. 1996, 2004, 2009) and stacked images (i.e.1996-2004 and 2004-2009) associated with the highest OIF values.

Table 5. Summary of the producer's accuracy of the different land use and land cover categories determined from the classification of the images of the individual years i.e. 1996, 2004 and 2009 and stacked images of 1996-2004 and 2004-2009 respectively.

Year Categories	1996	2004	2009	1996-2004	2004-2009
AG	98.66	98.54	98.68	99.83	99.7
NV	93.66	97.01	93.16	99.45	99.7
BL	100	100	100	100	100
SW	99.8	100	100	99.87	100
DB	96.41	92.21	95.5	96.31	96.53
MDB	74.34	63.44	68.93	85.31	86.26
LDB	70.75	61.21	77.99	92.72	97.48

AG: Agriculture; NV: Natural Vegetation; BL: Barren Land; SW: Standing Water; DB: Dense Built-up; MDB: Moderate Density Built-up; LDB: Low Density Built-up

Table 6. Summary of the producer's accuracy for different land use and land cover categories determined from the classification of the principal components of the images of the individual years i.e. 1996, 2004 and 2009 and stacked images of 1996-2004 and 2004-2009 respectively

Year Categories	1996	2004	2009	1996-2004	2004-2009
AG	99.6	98.87	99.66	99.85	99.78
NV	97.66	94.56	98.66	99.63	99.8
BL	100	100	100	100	100
SW	99.36	99.49	99.8	100	100
DB	97.51	91.88	96.25	98.31	99.28
MDB	67.57	63.47	68.93	85.75	87.26
LDB	69.44	69.09	78.62	93.05	97.48

Regression analysis between the producer's accuracy and OIF values for different band and PC combinations

In the present study, an attempt was made to determine if there exists any linear relationship between the producer's accuracy of the different categories and the OIF values of the various three-band combination and three-PC combination images that were classified to compute the producer's accuracy. In order to perform this task, linear regression coefficients were determined between the PAs of the individual categories with the OIF values of the corresponding three-band combination and three-PC combination images. The regression plots along with the regression coefficients (r^2) for the images of the individual years and stacked images are shown in Fig 3. The occurrence of r^2 value of 1 for a category would indicate that there exists perfect linear relationship between the PAs and OIF values in that image. Higher the value of the regression coefficient better is the relationship between the PAs and OIF values, which signifies that in such images OIF values have stronger influence on the PAs of the concerned categories. On the other hand, occurrence of the lower values of regression coefficients indicates that in such images OIF values do not have significant influence on the producer's accuracy.

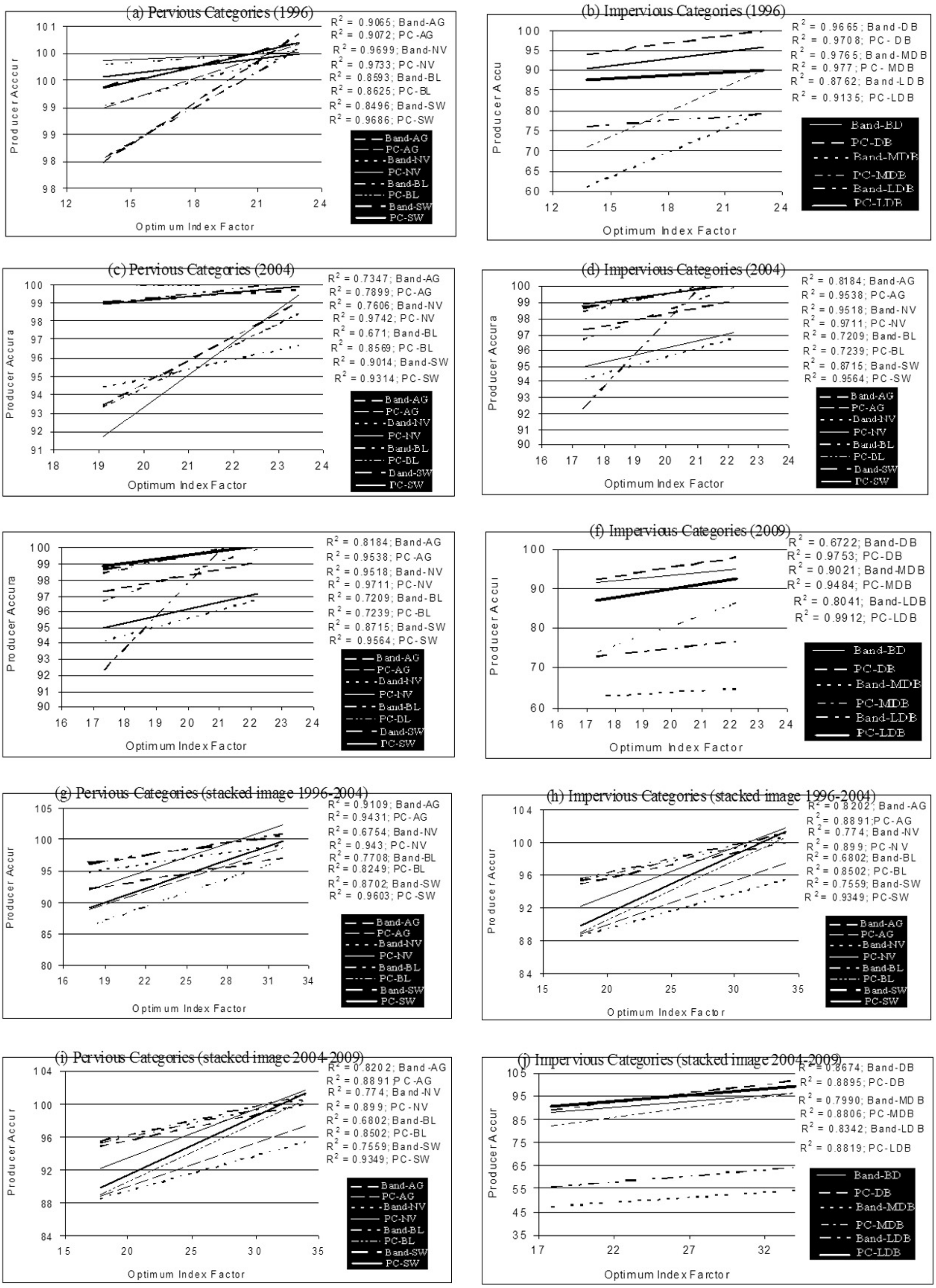

Fig 3. Regression analyses between the producer's accuracy and the OIF values of the various pervious and impervious categories for the images of the individual years (i.e. 1996, 2004, 2009) and stacked images (1996-2004 and 2004-2009)

Analyses of the regression coefficients determined between the PA of the various pervious and impervious categories with the corresponding OIF values in the images of the individual years (Fig 3) reveal the following observations. There occurs variable degree of relationship between the PAs and OIF values for the various pervious and impervious categories as depicted by the variation in the regression coefficient values in them. However, one conspicuous and common observation that stems out from the analyses is the occurrence of the significantly higher regression coefficient values in the various three-PC combination images as compared to their corresponding three-band combination images. Analyses of the regression coefficient values in the stacked images provide nearly similar observations as that of the images of the individual years. These observations indicate that the OIF values of the various three-band and three-PC combination images have significant relationship with the producer's accuracy of the different land use and land cover categories i.e. the three-band combination and three-PC combination images associated with the higher OIF values yield higher producer's accuracy.

Conclusions

As mentioned earlier, in the present research two different types of analyses have been performed. The first part comprises the comparative analyses among the producer's accuracy of the various pervious and impervious categories determined from the classification of the three-band and corresponding three-PC combination images having the highest OIF values generated from the images of the three individual years viz. 1996, 2004 and 2009 and two stacked images of the years i.e. 1996-2004 and 2004-2009 respectively. The second part comprises the regression analyses performed between the producer's accuracy of the different categories determined from the various three-band and three-PC combination images generated from the images of the individual years and stacked images and the corresponding OIF values of these three-band and three-PC combinations.

From these investigations, the following conclusions are drawn.

(1) The various pervious categories exhibit 100 percent producer's accuracy determined from the classification of the three-band and three-PC combination images having the highest OIF values. This was observed both in case of the images of the individual years as well as from the stacked images. The 100 percent producer's accuracy exhibited by the various pervious categories is attributed to the significantly considerable spectral homogeneity of the training signatures extracted for these categories from which the producer's accuracy is determined.

(2) Among the impervious categories, dense built-up exhibits higher producer's accuracy than the other two categories viz. moderate built-up and low density built-up categories.

(3) The three-PC combination images provide significantly higher producer's accuracy for the various categories than their corresponding three-band combination images.

(4) The producer's accuracy of the different categories determined from the classification of both the three-band and three-PC combination images having the highest OIF values are higher than that obtained from the classification of all the spectral bands and all the PCs.

(5) Regression analyses prove that the producer's accuracy of the different categories are linearly regressed with the OIF values of the three-band and three-PC combination images indicating the increase in the producer's accuracy with the corresponding increase in the OIF values.

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